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# OPTIMAL BOUNDS FOR INVERSE PROBLEMS WITH JACOBI-TYPE EIGENFUNCTIONS

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*Abstract:* We consider inverse problems where one wishes to recover an unknown function from the observation of a transformation of it by a linear operator, corrupted by an additive Gaussian white noise perturbation. We assume that the operator admits a singular value decomposition where the eigenvalues decay in a polynomial way, and where Jacobi polynomials appear as eigenfunctions. This includes, as an application, the well known Wicksell's problem. We establish asymptotic lower bounds for the minimax risk in a wide framework (i.e. with  $(L^p)_{1 < p < \infty}$  losses and Besov-like regularity spaces), which show that the estimator of Kerkyacharian, Picard, Petrushev, and Willer (2007) is quasi-optimal, and thus yield the minimax rates. We also establish some new results on the needlets introduced by Petrushev and Xu (2005) which appear as essential tools in this setting. Lastly we discuss the interest of the results concerning the treatment of inverse problems by wavelet procedures.

*Key words and phrases:* statistical inverse problems, minimax estimation, second-generation wavelets.

## 1. Motivation

We consider the problem of recovering a function  $f$  from a blurred and noisy version  $Y$ :

$$\forall v \in V, \quad Y(v) = (Kf, v)_V + \epsilon \xi(v),$$

where  $K$  is a linear operator between two Hilbert spaces:  $K : U \mapsto V$ ,  $\xi$  is a Gaussian white noise on  $V$ , and for  $H$  a Hilbert space and  $h_1, h_2 \in H$ ,  $(h_1, h_2)_H$  denotes the scalar product in  $H$  between  $h_1$  and  $h_2$ . We assume that  $f$  belongs to  $U = L^2([-1, 1], \mu(x)dx)$ , with  $\mu(x) = (1-x)^\alpha(1+x)^\beta$ ,  $\alpha, \beta > -1/2$ , and that  $K$  admits a singular value decomposition (SVD), i.e. there exists an orthonormal basis (called SVD basis) formed by the eigenfunctions of the self-adjoint operator  $K^*K$  (where  $K^*$  is the adjoint of  $K$ ). Moreover we assume that this SVD

basis consists of the classical Jacobi polynomials of type  $(\alpha, \beta)$ , and that the corresponding sequence of eigenvalues tend to zero at a polynomial rate. We will name such problems "Jacobi-type inverse problems".

The main motivation of this article is to establish asymptotic lower bounds for the minimax risk in a wide framework, considering  $L^p([-1, 1], \mu)$  losses, for all  $1 < p < \infty$ , and a Besov-like regularity space. This combined with the result of Kerkyacharian, Picard, Petrushev, and Willer (2007) (where upper bounds are provided) shows some new rate phenomenon for inverse problems.

### 1.1 What are the interests of the results?

The most popular technique for the treatment of inverse problems is probably singular value decomposition estimation, where the unknown function is expanded in the SVD basis, and the corresponding coefficients are estimated thanks to  $Y$ . Such techniques are very attractive theoretically and can be shown to be asymptotically minimax in many situations (see e.g. Mathe and Pereverzev (2003), Cavalier and Tsybakov (2002), Cavalier, Golubev, Picard, and Tsybakov (2002), Tsybakov (2000), Goldenshluger and Pereverzev (2003)). However there are limitations in the minimax framework, in particular such estimators generally cannot estimate functions exhibiting inhomogeneous regularity. To avoid this problem, several wavelet methods have been introduced during the last decade (for example Donoho (1995) and Abramovich and Silverman (1998)), which are minimax over wide sets of target functions, for example Besov spaces. Nevertheless such methods apply only to a category of inverse problems where the operator is well adapted to the structure of "first generation" wavelets, which are built from a Fourier analysis perspective. Thus many wavelet estimators are available whenever the operator displays some convolution structure (see for instance Pensky and Vidakovic (1999), Fan and Koo (2002), Kalifa and Mallat (2003)).

The main interest of our results is to grapple with quite different inverse problems, where the operator displays a polynomial structure. Then classical wavelets cannot be used, and new estimation techniques were given by Kerkyacharian, Picard, Petrushev, and Willer (2007): one uses new wavelets built upon polynomials (termed needlets, and introduced by Petrushev and Xu (2005)) to

develop the "NEEDD" estimator, and new spaces (which appear as an adaptation of the classical Besov spaces) to assess its performances. Here we establish a lower bound for the minimax risk, which matches with the rates of convergence of NEEDD (up to log factors). Consequently we obtain the minimax rates in all the Jacobi-type inverse problems, and we prove the quasi optimality of NEEDD. Note also that the results are established for all  $L^p([-1, 1], \mu)$  losses whereas in most other works cited previously, only the case  $p = 2$  is considered, with one exception: for the deconvolution problem in a periodic setting, Johnstone, Kerkycharian, Picard, and Raimondo (2004) combined with Willer (2005) established the minimax rates for all  $L^p([0, 1], dx)$  losses and over Besov spaces. We will draw a parallel between those rates and the ones obtained here: we exhibit elbow effects, and we show that the rates in the deconvolution model appear as a critical case of the rates in the Jacobi-type model. Moreover, we also give an application of our results to Wicksell's problem, which satisfies the required assumptions on the operator. This problem concerns the recovery of the density of the radii of spherical particles, when a sample of planar cuts is given, and has many applications in medicine and in biology.

In this paper, we have only considered standard inverse problems, where the operator is known. Recently, SVD or wavelet estimators have also been developed for noisy operators (see e.g. Efremovich and Koltchinskii (2001), Cavalier and Hentgartner (2005), Cavalier and Raimondo (2007) or Hoffmann and Reiss (2007)), and it may be interesting in the future to expand our results to that setting.

## 1.2 Which difficulties are met to prove the results?

The main idea behind NEEDD is to decompose the problem by using a family of functions (the needlets) which in some sense "both quasi-diagonalizes the operator  $K$  and the prior information on  $f$ " (to use Donoho's terms in Donoho (1995)). In the lower bound problem treated here, a similar problem arises, as we need a family of functions  $\{f_\lambda, \lambda \in \Lambda\} \subset \mathcal{U}$  representative of the difficulties of estimation inside the regularity space considered for the risk. This means that the functions  $f_\lambda$  must be chosen such that:

- they are distant from one another in  $L^p(\mu)$  norm,

- at the same time the distributions of the associated processes  $Y$  are close to one another (in a Kullback sense, for example).

A natural way to build such hypotheses is to use functions which enjoy localization properties, and whose images by  $K$  can be easily studied, and thus here again needlets are an essential tool. The hypotheses are built as linear combinations of such functions, with some parameters left free, which we adjust optimally with respect to the two constraints cited above. Then the minimal  $L^p(\mu)$  distance between the hypotheses yields the lower bound on the whole regularity space. This approach combining wavelets and lower bound techniques is classical (see Tsybakov 2004), but the main tool used here - the needlets - is quite unusual: their properties are still not thoroughly known, and in several ways they do not behave like classical wavelets. Thus in section 5.4 we give a brief list of needlet properties used to prove our results, some of which are established here. We show that, in particular, the non orthogonality of the needlets and the heterogeneity of their  $L^p(\mu)$  norms makes the lower bound problem more difficult than in other inverse problems, such as deconvolution for example (for which a proof using the classical Meyer wavelets can be found in Willer (2005)).

The paper is organized as follows. In section 2 we describe the model and state the main result, in section 3 we give an application to the Wicksell's problem, and in section 4 we discuss the interests of the results among the literature on inverse problems. Lastly in section 5 we give the proof of the main theorem, along with a description of the needlets where some new properties are established.

## 2. Main result

### 2.1 Model and assumptions

We are interested in nonparametric inverse problems in white noise, with a polynomial structure of the operator. We define this framework as follows. Let  $f$  be an unknown function belonging to the Hilbert space  $\mathcal{U} = L^2([-1, 1], \mu(x)dx)$ , with  $\mu(x) = (1 - x)^\alpha(1 + x)^\beta$ ,  $\alpha, \beta > -1/2$ . The estimation problem consists in recovering a good approximation of the function  $f$  from the observation of the random variable  $Y$  corresponding to a blurred and noisy version of  $f$ :

$$\forall v \in V, \quad Y(v) = (Kf, v)_V + \epsilon \xi(v). \quad (2.1)$$

**Blurring effect:** Let  $I = [a, b]$  or  $I = [a, b[$ , with  $-\infty < a < b \leq \infty$ , and  $\lambda : I \mapsto \mathbb{R}_+^*$  a continuous function. We set  $V = L^2(I, \lambda(x)dx)$ . Let  $K : \mathcal{U} \mapsto V$  be a linear operator satisfying the two following conditions. First assume  $K^*K$  (where  $K^*$  denotes the adjoint of  $K$ ) is diagonalizable, with a countable set of eigenvalues (denoted  $(b_k^2)_{k \in \mathbb{N}}$ ) which are strictly positive and decrease at a polynomial rate for some ill posedness coefficient  $\nu > 0$  (for two positive sequences  $(u_k)$  and  $(v_k)$ , the notation  $u_k \asymp v_k$  means that there exist  $0 < c_1 \leq c_2 < \infty$  such that  $c_1 v_k \leq u_k \leq c_2 v_k$ ):

$$\forall k \in \mathbb{N}^*, \quad b_k \asymp k^{-\nu}.$$

Secondly, assume that the classical Jacobi polynomials normalized in  $\mathcal{U}$  (we denote by  $P_k^{\alpha, \beta}$  or simply  $P_k$  the polynomial of degree  $k$ ) appear as an orthonormal basis of eigenfunctions of  $K^*K$ . So  $P_k$  is the polynomial of degree  $k$  such that  $\int_{-1}^1 P_k P_l d\mu = \delta_{k,l}$ , and we have:

$$\forall k \in \mathbb{N}, \quad K^*K P_k = b_k^2 P_k.$$

**Noise effect:**  $\epsilon > 0$  is deterministic, and  $\xi$  is a Gaussian white noise on  $V$ , i.e.:

$$\forall v, w \in V, \quad \begin{cases} \xi(v) \sim \mathcal{N}(0, \|v\|_V^2), \\ E[\xi(v)\xi(w)] = (v, w)_V. \end{cases}$$

## 2.2 Minimax rates

The aim of the paper is to establish the asymptotic minimax rates (when  $\epsilon \rightarrow 0$ ) for inverse problems described above, in a wide framework, i.e. for numerous choices of functions  $f$  and of measures of estimation errors. For the latter, we consider all  $\mathbb{L}^p(\mu)$  losses (for any  $1 < p < +\infty$ ) defined by:  $\forall u \in \mathcal{U}$ ,  $\|u\|_{\mathbb{L}^p(\mu)} = [\int_{-1}^1 |u(x)|^p d\mu(x)]^{\frac{1}{p}}$ . Concerning the target functions, we introduce spaces  $B_{\pi, r}^s(M)$  below, which appear as an adaptation of the classical Besov spaces. Let  $(\psi_{j, \eta})_{j \geq 0, \eta \in \mathbb{Z}_j}$  denote the tight frame of needlets described in section 5.4. For any  $f \in \mathcal{U}$ , we have the following decomposition:

$$f = \sum_{j \geq 0} \sum_{\eta \in \mathbb{Z}_j} \beta_{j\eta} \psi_{j\eta}, \quad \text{where } \beta_{j\eta} = (f, \psi_{j\eta})_{\mathcal{U}}.$$

Then for  $\pi \geq 1$ ,  $s \geq 1/\pi$ ,  $r \geq 1$ ,  $M > 0$  we define:

$$B_{\pi, r}^s(M) = \{f \in \mathcal{U} \mid \|(2^{js} (\sum_{\eta \in \mathbb{Z}_j} |\beta_{j, \eta}|^\pi \|\psi_{j, \eta}\|_\pi^\pi)^{1/\pi})_{j \geq -1}\|_{l^r} \leq M\}.$$

If  $\psi_{j,\eta}$  were a classical wavelet, then  $B_{\pi,r}^s$  would correspond to Besov spaces (see e.g. Härdle, Kerkycharian, Picard, and Tsybakov (1998)), which are very general regularity spaces including as particular cases Sobolev and Holder spaces, and which can be described very simply, thanks to any regular enough wavelet basis. Such spaces are widely used to study the theoretical performances of wavelet estimators in appropriate inverse problems. However here  $B_{\pi,r}^s$  correspond to new spaces, characterized by needlets, and appear as a natural alternative to the classical Besov spaces when the inverse problem does no longer possess a convolution structure, but a polynomial structure. Details on the space in this case can be found in Narcowich, Petrushev, and Ward (2006) and in the appendix of Kerkycharian, Picard, Petrushev, and Willer (2007).

We are interested in the minimax risk defined by:

$$R_\epsilon(B_{\pi,r}^s(\mathcal{M}), \mathbb{L}^p(\mu)) := \inf_{\hat{f}} \sup_{f \in B_{\pi,r}^s(\mathcal{M})} \mathbb{E}_f(\|\hat{f} - f\|_{\mathbb{L}^p(\mu)}^p),$$

where the infimum is taken over all  $\sigma(Y(t))_{t \geq 0}$ -measurable estimators  $\hat{f}$ . The results of Kerkycharian, Picard, Petrushev, and Willer (2007), concerning the rates of convergence of the NEEDD estimator, give immediately an upper bound for the risk. This is Theorem 1, where we recall that  $\nu > 0$  is a rate of decay of the eigenvalues of the operator ( $b_k \asymp k^{-\nu}$ ), and that  $\alpha, \beta > -\frac{1}{2}$  are parameters characterizing  $\mathcal{U}$ .

**Theorem 1.** *For all  $1 < p < \infty$ ,  $\pi \geq 1$ ,  $r \geq 1$  and  $s > \max_{\gamma \in \{\alpha, \beta\}} \{\frac{1}{2} - 2(\gamma + 1)(\frac{1}{2} - \frac{1}{\pi}) \vee 2(\gamma + 1)(\frac{1}{\pi} - \frac{1}{p}) \vee 0\}$  there exists  $C > 0$  such that:*

$$R_\epsilon(B_{\pi,r}^s(\mathcal{M}), \mathbb{L}^p(\mu)) \leq C[\log(1/\epsilon)]^{p+1}[\epsilon \sqrt{\log(1/\epsilon)}]^{\zeta p},$$

where  $\zeta = \min\{\zeta(s), \zeta(s, \alpha), \zeta(s, \beta)\}$  with:

$$\zeta(s) = \frac{s}{s + \nu + \frac{1}{2}}, \quad \zeta(s, \gamma) = \frac{s - 2(1 + \gamma)(\frac{1}{\pi} - \frac{1}{p})}{s + \nu + 2(1 + \gamma)(\frac{1}{2} - \frac{1}{\pi})}.$$

The main purpose of the paper is to prove that these rates coincide with the rates of the minimax risk up to log factors. We will establish the following theorem:

**Theorem 2.** *For all  $1 < p < \infty$ ,  $\pi \geq 1$ ,  $r \geq 1$  and  $s \geq 1/\pi$  there exists  $C > 0$  such that:*

$$R_\epsilon(B_{\pi,r}^s(\mathcal{M}), \mathbb{L}^p(\mu)) \geq C\epsilon^{\zeta p},$$

where  $\zeta = \min\{\zeta(s), \zeta(s, \alpha), \zeta(s, \beta)\}$  with:

$$\zeta(s) = \frac{s}{s + \gamma + \frac{1}{2}}, \quad \zeta(s, \gamma) = \frac{s - 2(1 + \gamma)(\frac{1}{\pi} - \frac{1}{p})}{s + \gamma + 2(1 + \gamma)(\frac{1}{2} - \frac{1}{\pi})}.$$

Note that the exact logarithmic factors of the minimax risk are not established yet. In this paper we have focused only on the main rate  $e^\zeta$ , so our results prove that NEEDD is "quasi optimal" in the Jacobi-type models.

### 3. Application to the Wicksell's problem

The Jacobi-type inverse models considered in this paper find applications in practice, in particular with the well known Wicksell's problem (Wicksell (1925)), which corresponds to the following situation. Suppose a population of spheres is embedded in a medium, with radii that may be assumed to be drawn independently from a density  $f$ . A random plane slice is taken through the medium, and some spheres are intersected by it. They furnish circles, the radii of which yield the points of observation  $Y_1, \dots, Y_n$ , as illustrated in Figure 3.1. The unfolding problem is to determine the density of the spheres radii from the observed circle radii. This problem arises in medicine, where the spheres might be tumors in an animal's liver (Nychka, Wahba, Goldfarb, and Pugh (1984)), as well as in numerous other contexts (biological, engineering, etc.) see for instance Cruz-Orive (1983).

If one uses the Lebesgue measure, then by a conditioning argument (see Wicksell (1925)) and under some assumptions, the density of the circles radii is:  $\forall y \in [0, 1], \quad K_0 f(y) = y \int_y^1 (x^2 - y^2)^{-1/2} f(x) dx$  (up to a constant). However few articles use this precise formulation of the problem. In the sequel we adopt the version proposed by Johnstone and Silverman (1991) who replaced the Lebesgue measure by two weighted measures. So we observe  $Y$  following model (2.1) with  $K : \tilde{U} \mapsto V$  given by:

$$\begin{cases} \tilde{U} = L^2([0, 1], \tilde{\mu}(x) dx), & \tilde{\mu}(x) = (4x)^{-1}, \\ V = L^2([0, 1], \lambda(y) dy), & \lambda(y) = 4\pi^{-1}(1 - y^2)^{1/2}, \\ Kf(y) = \frac{\pi}{4} y (1 - y^2)^{-1/2} \int_y^1 (x^2 - y^2)^{-1/2} f(x) d\tilde{\mu}(x). \end{cases}$$

Johnstone and Silverman (1991) show that  $K^*K$  admits the following root eigenvalues and eigenfunctions:  $b_k = \frac{\pi}{16}(1 + k)^{-1/2}$ ,  $\tilde{P}_k(x) = 4(k + 1)^{1/2} x^2 P_k^{0,1}(2x^2 -$



1). Thus up to changes in the variables (cf  $\tilde{\mathbf{U}}$  instead of  $\mathbf{U}$ , and hence the notations  $\tilde{\mathbf{P}}$  and  $\tilde{\mathbf{B}}_{\pi,r}^s$  later on), this is a Jacobi type inverse problem with  $(\alpha, \beta, \gamma) = (0, 1, 1/2)$ . Our results show that NEEDD is a quasi optimal estimator, and Theorem 1 and Theorem 2 establish the rates for the minimax risk  $\mathbf{R}_\epsilon^{\text{Wick}}$ . Neglecting  $\log(1/\epsilon)$  factors, we have  $\mathbf{R}_\epsilon^{\text{Wick}}[\tilde{\mathbf{B}}_{\pi,r}^s(\mathbf{M}), \mathbb{L}^p([0, 1], x^{3-2p} dx)] \asymp \epsilon^{\zeta_p}$ , where:

$$\zeta = \min\left\{\frac{s}{s+1}, \frac{s-2(\frac{1}{\pi}-\frac{1}{p})}{s+\frac{3}{2}-\frac{2}{\pi}}, \frac{s-4(\frac{1}{\pi}-\frac{1}{p})}{s+\frac{5}{2}-\frac{4}{\pi}}\right\}.$$

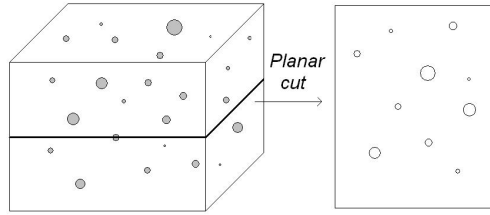


Figure 3.1: Wicksell's problem: observation of radii of disks after a planar cut of spheres

Thus we find rates which are new in the literature on Wicksell's problem, but of course several comments need to be done. First we used a transformation, initiated by Johnstone and Silverman (1991), of the original Wicksell problem. Other statistical results are available, but stated in yet another version of the problem, where one considers the *squared* radii of circles and spheres. Then a thorough minimax study can be found in Golubev and Levit (1998) for the estimation of the corresponding distribution function, and in Antoniadis, Fan, and Gijbels (2001) convergence rates are established for a wavelet density estimator, but only in  $\mathbb{L}^2([0, 1], dx)$  norm and over particular Besov spaces. Secondly we assumed that the random perturbation is a Gaussian white noise on the space  $V$  introduced above, and not a density perturbation as in the original problem. So here we add to the variety of theoretical results on Wicksell: we draw a complete picture of the problem in a minimax perspective, but by using a rather unusual representation. Work still needs to be done to extend our results to a more practical setting: research in that direction is initiated in Chapter 5 of Willer (2006), but a more thorough investigation is under study.

#### 4. Discussion

In the literature on statistical inverse problems, there are few results in a minimax framework as general as the one considered in this paper. Usually, only the  $L^2$  case is considered, and under the polynomial decay assumption of the eigenvalues, the rate  $\zeta = \frac{s}{s+\nu+1/2}$  (named "regular" rate) appears frequently (see Cavalier and Tsybakov (2002)). For more general  $L^p$  losses, only the case of deconvolution in a periodic setting (up to our knowledge) has been studied in Johnstone, Kerkycharian, Picard, and Raimondo (2004) and Willer (2005), and elbow effects appear, with a second rate named "sparse". It is interesting to draw a parallel between such a problem, where classical wavelets are widely used tools, and polynomial type problems, which require needlets.

For the deconvolution problem, minimax rates have been established for all  $L^p([0, 1], dx)$  losses ( $1 < p < \infty$ ) and over balls of a Besov space characterized by parameters  $\pi \geq 1$ ,  $s \geq 1/\pi$ ,  $r \geq 1$  as above. Then the rates are given as in Theorem 1 and 2 (up to the logarithmic factors) with  $\zeta$  replaced by:

$$\zeta = \min\{\zeta_{\text{regular}} := \frac{s}{s + \nu + 1/2}, \quad \zeta_{\text{sparse}} := \frac{s - 1/\pi + 1/p}{s + \nu + 1/2 - 1/\pi}\}.$$

Then the deconvolution setting appears as a critical case of the Jacobi setting, if we set  $\alpha = \beta = -\frac{1}{2}$ . More generally if we set  $\alpha = \beta > -\frac{1}{2}$  we can draw the cartography of the regular and sparse zones with respect to  $(p, \pi)$  (see figure 4.2), as was done in Härdle, Kerkycharian, Picard, and Tsybakov (1998) in the direct observation case. In the deconvolution case (i.e. the "wavelet scenario") the separation between the zones is linear, whereas in the "Jacobi scenario" the critical case is more complicated. So in that scenario we find new rates, and note that this novelty is not an artifact stemming from the weights on the space, since in the Lebesgue case the rates for the Jacobi scenario (i.e.  $\alpha = \beta = 0$ ) do not coincide with those of the wavelet scenario. Thus the origin of the differences lies in the polynomial structure of the inverse problems, in opposition to the convolution structure of the problems usually treated by first generation wavelet methods.

These results illustrate the fact that the limitations met by classical wavelets in inverse problem theory, concerning the type of operators involved, can be circumvented by using new wavelet constructions such as needlets. Similarly

other second generation wavelets, meaning wavelets which do not rely on Fourier type constructions, may help to break new ground in statistical inverse problems.

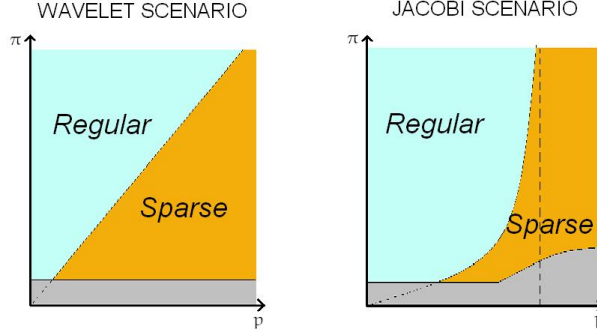


Figure 4.2: Cartography of the regular and sparse zones with respect to  $(p, \pi)$  in the deconvolution case (left) and in the Jacobi case if  $\alpha = \beta = 0$  (right)

## 5. Proofs

### 5.1 General scheme of the proof

The proof of Theorem 2 requires well known methods for minimax lower bounds, as available in Tsybakov (2004), combined with new tools (i.e. needlets). We use Theorem 5.2 in Tsybakov (2004), which involves the Kullback-Leibler divergence  $\mathcal{K}(P, Q)$  between two probability measures  $P$  and  $Q$ , defined by:

$$\mathcal{K}(P, Q) = \begin{cases} \int \ln\left(\frac{dP}{dQ}\right) dP, & \text{if } P \ll Q; \\ +\infty, & \text{otherwise.} \end{cases}$$

Changing the notations, and replacing slightly the conditions so as to include the case  $m = 1$  (the result remains true using  $\tau = 1/\sqrt{m+1}$  instead of  $\tau = 1/\sqrt{m}$  in the proof), this theorem states that:

**Theorem 3.** *Assume there exist  $m+1$  functions  $f_0, \dots, f_m$  (with  $m \geq 1$ ) satisfying the three following conditions:*

- **Condition (i):** for all  $i \in \{0, 1, \dots, m\}$ ,  $f_i \in B_{\pi, r}^S(M)$ ,
- **Condition (ii):** for all  $i \neq j$ ,  $\|f_i - f_j\|_p^p \geq 2\delta$  for some  $\delta > 0$ ,
- **Condition (iii'):** for all  $i \in \{1, \dots, m\}$ ,  $P_{f_i} \ll P_{f_0}$  and  $\frac{1}{m} \sum_{i \geq 1} \mathcal{K}(P_{f_i}, P_{f_0}) \leq$

$\theta \log(M+1)$ , where  $0 < \theta < \frac{1}{8}$  and  $P_f$  denotes the probability distribution of the process  $Y$  under the hypothesis  $f$ .

Then  $\inf_{\hat{f}} \sup_{f \in B_{\pi, r}^s(M)} P_f(\|\hat{f} - f\|_p^p \geq \delta) \geq \pi_0$ , where  $\pi_0$  is a positive universal constant.

Let us precise condition (iii') in model 2.1. Let  $I = [a, b]$  (the case  $I = [a, b[$  is similar). If we define the variables  $\tilde{Y}(w) = Y(w(\cdot - a)/\sqrt{\lambda(\cdot)})$  and  $\tilde{\xi}(w) = \xi(w(\cdot - a)/\sqrt{\lambda(\cdot)})$  for all  $w \in \tilde{V} = \mathbb{L}^2([0, b-a], dx)$  then model 2.1 is equivalent to:  $\tilde{Y}(w) = (Kf(\cdot + a)\sqrt{\lambda(\cdot + a)}, w)_{\tilde{V}} + \epsilon \tilde{\xi}(w)$ , which is equivalent to the stochastic equation:  $\forall t \in [0, b-a], d\tilde{Y}_t = Kf(\cdot + a)\sqrt{\lambda(\cdot + a)} + \epsilon dW_t$  where  $(W_t)_{t \geq 0}$  denotes the standard Wiener process. Then using Girsanov's formula, for all  $f, g \in \mathcal{U}$ ,  $P_f$  is absolutely continuous with respect to  $P_g$ , and under the hypothesis  $g$  the likelihood ratio  $\Lambda_\epsilon(f, g) := \frac{dP_f}{dP_g}(Y)$  is distributed as:  $\log \Lambda_\epsilon(f, g) \sim \mathcal{N}(-\frac{1}{2} \|\frac{K(f-g)}{\epsilon}\|_{\tilde{V}}^2, \|\frac{K(f-g)}{\epsilon}\|_{\tilde{V}})$ . Thus

$$\mathcal{K}(P_f, P_g) = E_f \ln(\Lambda_\epsilon(f, g)) = -E_f \log(\Lambda_\epsilon(g, f)) = \frac{1}{2} \|\frac{K(f-g)}{\epsilon}\|_{\tilde{V}}^2.$$

Then condition (iii') can be replaced by the sufficient condition (iii):

**Condition (iii):**  $f_0 = 0$  and for all  $i \in \{1, \dots, m\}$ ,  $\|Kf_i\|_{\tilde{V}}^2 \leq \theta \log(M+1)\epsilon^2$  where  $0 < \theta < \frac{1}{4}$ .

We use Theorem 3 by building several sets of hypotheses  $\{f_i, i = 0, 1, \dots, m\}$  satisfying the three conditions. Then using Chebychev's inequality we have:

$$\inf_{\hat{f}} \sup_{f \in B_{\pi, r}^s(M)} E_f \|\hat{f} - f\|_p^p \geq \pi_0 \delta.$$

With an appropriate choice of three sets  $\{f_i, i = 0, 1, \dots, m\}$  depending on the level of noise  $\epsilon$ ,  $\delta$  yields the three expected rates. We detail the sparse cases in section 5.2 and then the regular case in 5.3. Throughout these two sections, we use many (old or new) preliminary results on the needlets, all of which are given in section 5.4.

## 5.2 Sparse cases

The sparse rates  $\mu(\alpha)$  and  $\mu(\beta)$  are obtained respectively by applying Theorem 3 to the following sets of functions:  $\{f_0 = 0, f_1 = \gamma\psi_{j_0, \eta_1}\}$ , and  $\{f_0 = 0, f_1 = \gamma\psi_{j_1, \eta_2, j_1}\}$ , for some parameters  $\gamma, j_0$  and  $j_1$  chosen so as to satisfy conditions (i) to (iii). We detail only the proof for  $\mu(\alpha)$  (the proof for  $\mu(\beta)$  is similar).

**Condition (i)** is satisfied if  $u_j := 2^{js}(\sum_{\eta \in \mathbb{Z}_j} |\langle f_1, \psi_{j, \eta} \rangle|^\pi \|\psi_{j, \eta}\|_\pi^\pi)^{1/\pi}$  belongs to  $l^r(M)$ , where  $f_1 = \gamma\psi_{j_0, \eta_1}$ . Using the first part of Lemma 1,  $u_j = 0$  whenever  $|j - j_0| \geq 2$ . So in the sequel we assume that  $j \in \{j_0 - 1, j_0, j_0 + 1\}$ , and the  $l^r$  norm of  $(u_j)$  is bounded by a constant  $M$  (independent of  $\gamma > 0$  and  $j_0$ ) if for instance  $u_j \leq 3^{-\frac{1}{r}} M$ . We have:  $u_j^\pi = 2^{j\pi s} \gamma^\pi \sum_{\eta \in \mathbb{Z}_j} |\langle \psi_{j_0, \eta_1}, \psi_{j, \eta} \rangle|^\pi \|\psi_{j, \eta}\|_\pi^\pi \leq c(I_1 + I_2)$ , with, using the bound of Theorem 6:

$$I_1 = 2^{j[\pi s + (\pi-2)(\alpha+1)]} \gamma^\pi \sum_{k=1}^{2^{j-1}} |\langle \psi_{j_0, \eta_1}, \psi_{j, \eta} \rangle|^\pi k^{-(\pi-2)(\alpha+1/2)},$$

$$I_2 = 2^{j[\pi s + (\pi-2)(\beta+1)]} \gamma^\pi \sum_{k=2^{j-1}+1}^{2^j} |\langle \psi_{j_0, \eta_1}, \psi_{j, \eta} \rangle|^\pi (2^j - k + 1)^{-(\pi-2)(\beta+1/2)}.$$

Using the second part of Lemma 1, we have for any  $\zeta$ :  $|\langle \psi_{j_0, \eta_1}, \psi_{j, \eta_k} \rangle| \leq c \frac{1}{k^\zeta}$ . Thus choosing any  $\zeta > \frac{-(\pi-2)(\alpha+1/2)+1}{-(\pi-2)(\beta+1/2)}$ , we obtain:  $I_1 \leq c 2^{j[\pi s + (\pi-2)(\alpha+1)]} \gamma^\pi$ . Moreover  $\sum_{k=1}^{2^{j-1}} \frac{(2^j - k + 1)^{-(\pi-2)(\beta+1/2)}}{k^\zeta \pi} \leq c 2^{-\zeta \pi j} 2^{j[1 - (\pi-2)(\beta+1/2)]_+}$ , so for a large enough  $\zeta$ :  $I_2 \leq c 2^{j[\pi s + (\pi-2)(\beta+1) - \zeta \pi + [1 - (\pi-2)(\beta+1/2)]_+]} \gamma^\pi \leq c I_1$ . Thus we have for all  $j \in \{j_0 - 1, j_0, j_0 + 1\}$ :  $u_j^\pi \leq c 2^{j_0[\pi s + (\pi-2)(\alpha+1)]} \gamma^\pi$ , and condition (i) is satisfied if, for a small enough  $c$  depending on  $M$ :

$$\gamma \leq c 2^{-j_0[s + (1 - \frac{2}{\pi})(\alpha+1)]}.$$

**Condition (ii)**, using theorem 6, is fulfilled with:  $\delta \asymp \gamma^p 2^{j_0(p-2)(\alpha+1)}$ .

**Condition (iii)** is satisfied if:  $\int_I (\frac{K(\gamma\psi_{j_0, \eta_1})(t)}{\epsilon})^2 d\lambda(t) \leq C$ . We have  $\psi_{j_0, \eta}(x) = \sum_{l=2^{j-2}+1}^{2^j-1} c_{j, \eta, l} P_l(x)$  and  $K^* K P_l = b_l^2 P_l$ , thus:

$$\|K(\psi_{j_0, \eta_1})\|_V^2 = \sum_l [b_l c_{j, \eta, l}]^2 \asymp 2^{-2\nu j_0} \sum_l [c_{j, \eta, l}]^2 = 2^{-2\nu j_0} \|\psi_{j_0, \eta_1}\|_U^2 \leq C 2^{-2\nu j_0}.$$

So condition (iii) is satisfied if  $\frac{\gamma 2^{-\nu j_0}}{\epsilon} \leq c$ .

In view of the three conditions, we set  $\gamma = c\epsilon 2^{j_0}$  with a small enough  $c$ , and  $2^{j_0} \asymp \epsilon^{-\frac{1}{s+\nu+(1-\frac{2}{\pi})(\alpha+1)}}$ . Then  $\delta \asymp \epsilon^{\frac{p[s+2(\frac{1}{p}-\frac{1}{\pi})(\alpha+1)]}{s+\nu+(1-\frac{2}{\pi})(\alpha+1)}}$  gives the sparse lower bound.

### 5.3 Regular case

Let  $m$  be an integer such that  $2^m \geq n_2$ , where  $n_2$  is the integer from Theorem 7 in the case  $p = 2$ . For some parameters  $\gamma$  and  $j_0 \geq m + 1$  chosen further, we consider for  $\epsilon \in \{0, 1\}^{2^{j_0-m-1}}$  the  $2^{j_0-m-1}$  functions:

$$f_\epsilon = \gamma \sum_{k=1}^{2^{j_0-m-1}} \epsilon_k k^\delta \psi_{j_0, \eta_{2^m k}},$$

for some  $\delta$  satisfying:  $\delta > \max[1, \alpha + 1/2, (1 - \frac{2}{\pi})(\alpha + \frac{1}{2}) - \frac{1}{\pi}]$ . We only keep some of these functions. By Varshamov-Gilbert theorem (see for instance Tsybakov (2004)), there exists a subset  $E_{j_0} = \{\epsilon^0, \dots, \epsilon^{T_{j_0}}\}$  of  $\{0, 1\}^{2^{j_0-m-1}}$  and two constants  $c > 0$ ,  $\rho > 0$  such that  $\forall 0 \leq u < v \leq T_{j_0}$ :

$$\sum_{k=1}^{2^{j_0-m-1}} |\epsilon_k^u - \epsilon_k^v| \geq c 2^{j_0}, \quad T_{j_0} \geq \exp(\rho 2^{j_0}) \quad \text{and} \quad f_{\epsilon^0} = 0.$$

In the sequel we consider the set  $\{f_\epsilon, \quad \epsilon \in E_{j_0}\}$ .

**Condition (i):** for  $\epsilon \in E_{j_0}$ , let  $u_j := 2^{js}(\sum_{\eta \in \mathbb{Z}_j} |\langle f_\epsilon, \psi_{j, \eta} \rangle|^\pi \|\psi_{j, \eta}\|_\pi^\pi)^{1/\pi}$ . Once again  $u_j = 0$  whenever  $|j - j_0| \geq 2$ . Now let  $j \in \{j_0 - 1, j_0, j_0 + 1\}$ . Then we have:  $u_j^\pi \leq c(I_1 + I_2)$ , with:

$$I_1 = 2^{j[\pi s + (\pi-2)(\alpha+1)]} \gamma^\pi \sum_{k=1}^{2^{j-1}} k^{-(\pi-2)(\alpha+1/2)} \left( \sum_{l=1}^{2^{j_0-1}} l^\delta |\langle \psi_{j_0, \eta_l}, \psi_{j, \eta_k} \rangle| \right)^\pi,$$

$$I_2 = 2^{j[\pi s + (\pi-2)(\beta+1)]} \gamma^\pi \sum_{k=2^{j-1}+1}^{2^j} (2^j - k + 1)^{-(\pi-2)(\beta+1/2)} \left( \sum_{l=1}^{2^{j_0-1}} l^\delta |\langle \psi_{j_0, \eta_l}, \psi_{j, \eta_k} \rangle| \right)^\pi.$$

Using Lemma 1 with some  $\zeta$  given later, we have  $|\langle \psi_{j_0, \eta_l}, \psi_{j, \eta_k} \rangle| \leq c \frac{1}{(1+|l-2^{j_0-j}k|)^\zeta}$ .

Then, for  $x \in \mathbb{R}$ , let  $\lfloor x \rfloor$  denote the largest integer smaller than  $x$ . We have:

$$\sum_{l \leq \lfloor 2^{j_0-j}k \rfloor} \frac{l^\delta}{(1+|l-2^{j_0-j}k|)^\zeta} \leq c k^\delta \sum_{l \leq \lfloor 2^{j_0-j}k \rfloor} \frac{1}{(1+\lfloor 2^{j_0-j}k \rfloor - l)^\zeta} \leq c k^\delta \sum_{l \geq 1} \frac{1}{l^\zeta} \leq c k^\delta,$$

for a large enough  $\zeta$ . Moreover:

$$\begin{aligned} \sum_{l \geq \lfloor 2^{j_0-j} k \rfloor + 1} \frac{l^\delta}{(1 + |l - 2^{j_0-j} k|)^\zeta} &\leq \sum_{l \geq \lfloor 2^{j_0-j} k \rfloor + 1} \frac{l^\delta}{(l - \lfloor 2^{j_0-j} k \rfloor)^\zeta} = \sum_{l \geq 1} \frac{(l + \lfloor 2^{j_0-j} k \rfloor)^\delta}{l^\zeta} \\ &\leq c \sum_{l \geq 1} \frac{l^\delta + \lfloor 2^{j_0-j} k \rfloor^\delta}{l^\zeta} \leq C k^\delta, \end{aligned}$$

for  $\zeta$  large enough. To obtain the last line, we used the fact that  $\delta \geq 1$ . Thus

$$\sum_{l=1}^{2^{j_0-1}} \frac{l^\delta}{(1 + |l - 2^{j_0-j} k|)^\zeta} \leq c k^\delta, \text{ and:}$$

$$I_1 \leq c 2^{j[\pi s + (\pi-2)(\alpha+1)]} \gamma^\pi \sum_{k=1}^{2^{j-1}} k^{-(\pi-2)(\alpha+1/2)} k^{\delta\pi} = c 2^{j[s+\delta+\frac{1}{2}]} \gamma.$$

For  $I_2$  remark that for any  $k \in \{2^{j-1} + 1, \dots, 2^j\}$  and any  $l \in \{1, \dots, 2^{j_0-1}\}$ , we have:  $|\frac{k}{2^j} - \frac{l}{2^{j_0}}| = \frac{k}{2^j} - \frac{l}{2^{j_0}} \geq |\frac{2^j-k}{2^j} - \frac{l}{2^{j_0}}|$ . So for such a  $k$ , as previously:  $\sum_{l=1}^{2^{j_0-1}} \frac{l^\delta}{(1 + |l - 2^{j_0-j} k|)^\zeta} \leq \sum_{l=1}^{2^{j_0-1}} \frac{l^\delta}{(1 + |l - 2^{j_0-j} (2^j - k)|)^\zeta} \leq c(2^j - k)^\delta$ , and:

$$I_2 \leq c 2^{j[\pi s + (\pi-2)(\beta+1)]} \gamma^\pi \sum_{k=2^{j-1}+1}^{2^j} (2^j - k + 1)^{-(\pi-2)(\beta+1/2)} (2^j - k + 1)^{\delta\pi} = c 2^{j[s+\delta+\frac{1}{2}]} \gamma.$$

Finally we have  $u_j \leq c 2^{j[s+\delta+\frac{1}{2}]} \gamma$  so  $f_\varepsilon$  belongs to  $B_{\pi,r}^s(M)$  if, with a small enough  $c$  depending on  $M$ :

$$\gamma \leq c 2^{-j_0[s+\delta+\frac{1}{2}]}.$$

**Condition (ii):** for all  $u, v \in E_{j_0}$  with  $u \neq v$ ,  $f_u - f_v = \sum_{k=1}^{2^{j_0-m-1}} \gamma(\varepsilon_k^u - \varepsilon_k^v) k^\delta \psi_{j_0, n_{2^m k}}$ . So by Theorem 7 and Theorem 6, we have:

$$\|f_u - f_v\|_U^2 \geq c \gamma^2 \sum_{k=1}^{2^{j_0-m-1}} (\varepsilon_k^u - \varepsilon_k^v)^2 k^{2\delta} = c \gamma^2 \sum_{\{k \mid \varepsilon_k^u \neq \varepsilon_k^v\}} k^{2\delta}.$$

Let  $N_{u,v}$  denote the cardinal of the set  $\{k \in \{1, \dots, 2^{j_0-m-1}\} \mid \varepsilon_k^u \neq \varepsilon_k^v\}$ , then we have  $N_{u,v} \geq c 2^{j_0}$  and, since  $\delta > 0$ :

$$\|f_u - f_v\|_U^2 \geq c \gamma^2 \sum_{k=1}^{N_{u,v}} k^{2\delta} = \gamma^2 N_{u,v}^{1+2\delta} \geq c \gamma^2 2^{j_0(1+2\delta)}. \quad (5.1)$$

Let us distinguish two cases. Suppose  $2 < p < \infty$  and let  $1/p + 1/q = 1$ . By (5.1) and Hölder's inequality we have:

$$c 2^{j_0(1+2\delta)} \leq \|f_u - f_v\|_{\mathbb{L}^2(\mu)}^2 \leq \|f_u - f_v\|_{\mathbb{L}^p(\mu)} \|f_u - f_v\|_{\mathbb{L}^q(\mu)}.$$

Using Theorem 5 and the fact that, under our assumptions,  $q\delta - (q-2)(\alpha+1/2) > -1$ , we have:

$$\|f_u - f_v\|_{\mathbb{L}^q(\mu)} \leq c\gamma 2^{j_0 \frac{(q-2)}{q}(\alpha+1)} \left( \sum_{k=1}^{2^{j_0-m-1}} k^{q\delta - (q-2)(\alpha+1/2)} \right)^{1/q} \leq c'\gamma 2^{j_0(\frac{1}{2}+\delta)},$$

therefore  $\|f_u - f_v\|_{\mathbb{L}^p(\mu)}^p \geq c\gamma^p 2^{j_0 p(\frac{1}{2}+\delta)}$ .

Suppose now  $1 < p < 2$ , we have using (5.1):

$$c2^{j_0(1+2\delta)} \leq \|f_u - f_v\|_{\mathbb{L}^2(\mu)}^2 \leq \|f_u - f_v\|_{\mathbb{L}^p(\mu)}^p \|f_u - f_v\|_{\mathbb{L}^\infty(\mu)}^{2-p}.$$

From Theorem 4 we infer for all  $0 \leq \theta \leq \pi/2$ :

$$|\psi_{j_0, \eta_k}(\cos \theta)| \leq C \frac{2^{j_0(1+\alpha)}}{(1 + 2^{j_0}|\theta - \frac{k\pi}{2^{j_0}}|)^l} \frac{1}{(2^{j_0}\theta + 1)^{\alpha+1/2}},$$

so for  $l$  large enough:  $|\psi_{j_0, \eta_k}(\cos \theta)| \leq C \frac{2^{j_0(1+\alpha)}}{k^{\alpha+1/2}} \frac{1}{(1+2^{j_0}|\theta - \frac{k\pi}{2^{j_0}}|)^2}$  and, since  $\delta - (\alpha + 1/2) \geq 0$ :

$$|f_u(\cos \theta) - f_v(\cos \theta)| \leq c\gamma 2^{j_0(\alpha+1)} \sum_{k=1}^{2^{j_0-m-1}} k^{\delta - (\alpha+1/2)} \frac{1}{(1 + 2^{j_0}|\theta - \frac{k\pi}{2^{j_0}}|)^2} \leq c'\gamma 2^{j_0(\frac{1}{2}+\delta)},$$

where in the last line we used the fact that for any  $\theta$ ,  $\sum_{k=1}^{2^{j_0-m-1}} \frac{1}{(1+2^{j_0}|\theta - \frac{k\pi}{2^{j_0}}|)^2} \leq c \sum_{l=1}^{+\infty} \frac{1}{l^2}$ . Similarly the same bound holds for any  $\pi/2 \leq \theta \leq \pi$ , thus we have:  $\|f_u - f_v\|_{\mathbb{L}^\infty(\mu)} \leq c2^{j_0(\frac{1}{2}+\delta)}$ , and once again:  $\|f_u - f_v\|_{\mathbb{L}^p(\mu)}^p \geq c\gamma^p 2^{j_0 p(\frac{1}{2}+\delta)}$ .

**Condition (iii):** we have  $\sqrt{T_{j_0}} \geq \exp(\frac{\rho}{2}2^{j_0})$ , so (iii) is satisfied if for all  $\varepsilon^u \in E_{j_0}$ ,  $\int_I (\frac{K(f_u)(t)}{\varepsilon})^2 d\lambda(t) \leq c2^{j_0}$  for a small enough constant  $c$ . We have:  $f_u = \sum_{k=1}^{2^{j_0-m-1}} \beta_{j_0, k} \psi_{j_0, \eta_{2^m k}} = \sum_{k=1}^{2^{j_0-m-1}} \sum_{l \in \mathbb{N}} \beta_{j_0, k} c_{j_0, \eta_k, l} P_l(x)$ , with  $\beta_{j_0, k} = \gamma \varepsilon_k^u k^\delta$ . Thus:

$$\begin{aligned} \|K(f_u)\|_{\mathbb{L}^2(I, \lambda)}^2 &= \sum_l \left[ \sum_{k=1}^{2^{j_0-m-1}} \beta_{j_0, k} b_l c_{j_0, \eta_k, l} \right]^2 \asymp 2^{-2vj_0} \sum_l \left[ \sum_{k=1}^{2^{j_0-m-1}} \beta_{j_0, k} c_{j_0, \eta_k, l} \right]^2 \\ &= 2^{-2vj_0} \left\| \sum_{k=1}^{2^{j_0-m-1}} \beta_{j_0, k} \psi_{j_0, \eta_{2^m k}} \right\|_{\mathbb{L}^2(I, \mu)}^2 \leq c2^{-2vj_0} \sum_{k=1}^{2^{j_0-m-1}} \beta_{j_0, k}^2 \\ &\leq c2^{-2vj_0} \gamma^2 \sum_{k=1}^{2^{j_0-m-1}} k^{2\delta} = c2^{-2vj_0} \gamma^2 2^{(2\delta+1)j_0}. \end{aligned}$$



So finally we need:  $\frac{2^{-\nu j_0} \gamma 2^{(\delta + \frac{1}{2})j_0}}{\epsilon} \leq C 2^{j_0/2}$ , i.e.  $\frac{2^{(\delta - \nu)j_0} \gamma}{\epsilon} \leq C$  with a small enough constant  $C$ .

In view of the three conditions, we set  $2^{j_0} \asymp \epsilon^{-\frac{1}{s+\nu+\frac{1}{2}}}$  and  $\gamma \asymp \epsilon^{\frac{s+\delta+\frac{1}{2}}{s+\nu+\frac{1}{2}}}$ , and we obtain the lower bound:  $\delta \asymp \epsilon^{\frac{ps}{s+\nu+\frac{1}{2}}}$ .

#### 5.4 Description of Jacobi needlets

In this section we recall briefly the construction of Jacobi needlets introduced by Petrushev and Xu (2005), for more details we refer the reader to that paper. We recall that  $(P_k)$  denote the Jacobi polynomials normalized in  $\mathcal{U}$ . The first step of the construction consists of a Littlewood-Paley decomposition by using a family of operators whose kernels are of the form:  $\forall j \in \mathbb{N}$ ,  $\Lambda_j(x, y) = \sum_{k \in \mathbb{N}} a(k/2^j) P_k(x) P_k(y)$ . Here  $a(\cdot)$  is a  $C^\infty$  function supported in  $[-2, -\frac{1}{2}] \cup [\frac{1}{2}, 2]$  such that  $\sum_{j \geq 0} a^2(x/2^j) = 1$ ,  $\forall |x| \geq 1$ . Moreover we add the condition:  $a(x) > c > 0$  for  $3/4 \leq x \leq 7/4$  (so as to use results established in Kerkycharian, Picard, Petrushev, and Willer (2007)).

The second step is to use a quadrature formula for each resolution  $j$ , which involves as knots the zeros of the Jacobi polynomial  $P_{2^j}$ , denoted by  $\mathbb{Z}_j = \{\eta_k : k = 1, 2, \dots, 2^j\}$ , and as coefficients the Christoffel numbers (see Szegö (1975)), denoted by  $\{b_{j, \eta_k} : k = 1, 2, \dots, 2^j\}$ . We assume that  $\eta_k = \cos \theta_{j,k}$  are ordered so that  $\eta_1 > \eta_2 > \dots > \eta_{2^j}$ , and hence  $0 < \theta_{j,1} < \theta_{j,2} < \dots < \theta_{j,2^j} < \pi$ . It is well known that  $\theta_{j,k} \asymp \frac{k\pi}{2^j}$  and  $b_{j, \eta_k} \asymp 2^{-j} \omega_{\alpha, \beta}(2^j; \eta_k)$  with  $\omega_{\alpha, \beta}(2^j; x) := (1 - x + 2^{-2j})^{\alpha+1/2} (1 + x + 2^{-2j})^{\beta+1/2}$  (cf Szegö (1975)).

We finally define the Jacobi needlets as

$$\forall j \in \mathbb{N}, k \in \{1, \dots, 2^j\}, \quad \psi_{j, \eta_k}(x) = \sqrt{b_{j, \eta_k}} \Lambda_{2^j}(x, \eta_k).$$

In view of the support of  $a$ , the needlets depend on the Jacobi polynomials in the following way:  $\psi_{j, \eta}(x) = \sum_{l=2^{j-2}+1}^{2^j-1} c_{j, \eta, l} P_l(x)$ , with coefficients  $c_{j, \eta, l} = a(l/2^{j-1}) P_l(\eta) \sqrt{b_{j, \eta}}$ . Some examples of needlets are given on top of figure 5.3. Now we give a list of their properties needed to establish Theorem 2.

*Wavelet-like properties:* First of all, the needlets form a tight frame:

$$\forall f \in \mathbb{H}, \quad f = \sum_{j \in \mathbb{N}} \sum_{\eta \in \mathbb{Z}_j} \langle f, \psi_{j, \eta} \rangle \psi_{j, \eta} \quad \text{and} \quad \|f\|^2 = \sum_{j \in \mathbb{N}} \sum_{\eta \in \mathbb{Z}_j} |\langle f, \psi_{j, \eta} \rangle|^2.$$

Secondly each needlet  $\psi_{j,\eta_k}$  is concentrated on a small interval centered on  $\eta$ , as established in Petrushev and Xu (2005):

**Theorem 4.** *For any  $l \geq 1$  there exists a constant  $C_l > 0$  such that*

$$|\psi_{j,\eta_k}(\cos \theta)| \leq C_l \frac{1}{\sqrt{\omega_{\alpha,\beta}(2^j, \cos \theta)}} \frac{2^{j/2}}{(1 + 2^j |\theta - \frac{\pi k}{2^j}|)^l}, \quad 0 \leq \theta \leq \pi.$$

This almost exponential concentration property implies wavelet-like inequalities for the  $L^p$  norms of linear combinations of needlets. This is Theorem 5, established in Kerkycharian, Picard, Petrushev, and Willer (2007):

**Theorem 5.** *Let  $0 < p < \infty$ . Then there exists a constant  $C_p > 0$  such that for any collection of numbers  $\{\lambda_k : k = 1, 2, \dots, 2^j\}$ ,  $j \geq 0$ ,*

$$\left\| \sum_{k=1}^{2^j} \lambda_k \psi_{j,\eta_k} \right\|_{L^p(\mu)}^p \leq C_p \sum_{k=1}^{2^j} |\lambda_k|^p \|\psi_{j,\eta_k}\|_{L^p(\mu)}^p.$$

*Differences with first generation wavelets:* Needlets are not issued from a translation/dilatation scheme, hence major differences with classical wavelets. Let us for example describe the needlets at a given resolution level  $j$ . First they are not distributed uniformly on the interval, but around the  $\eta_k$ s. Second they behave quite differently depending on their locations  $\eta$  in the interval, which is reflected in Theorem 4 by the variations of the function  $\omega_{\alpha,\beta}(2^j, \cdot)$ . This is illustrated in figure 5.3: for a given resolution  $j$ , "edge" needlets have different shapes than "middle" needlets, and the  $L^p$  norms are not constant with respect to  $\eta$  (except arguably for  $p = 2$ ). More precisely concerning  $L^p$  norms, the following bounds have been established in Petrushev and Xu (2005) (for the upper bounds) and in Kerkycharian, Picard, Petrushev, and Willer (2007) (for the lower bounds). They play an important role for the proofs of Theorem 1 and 2.

**Theorem 6.**  *$\forall 0 < p \leq \infty, \forall j \in \mathbb{N}$ , we have up to scalars depending only on  $p$ :*

$$\begin{aligned} \forall 1 \leq k \leq 2^{j-1}, \quad & \|\psi_{j,\eta_k}\|_p \asymp \left( \frac{2^{j(\alpha+1)}}{k^{\alpha+1/2}} \right)^{1-2/p}, \\ \forall 2^{j-1} < k \leq 2^j, \quad & \|\psi_{j,\eta_k}\|_p \asymp \left( \frac{2^{j(\beta+1)}}{(1 + (2^j - k))^{\beta+1/2}} \right)^{1-2/p}. \end{aligned}$$

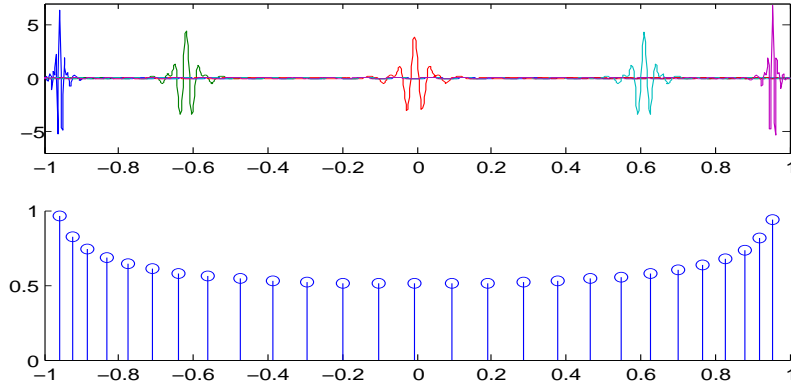


Figure 5.3: For a given resolution  $j$ : some of the needlets  $\psi_{j,\eta_k}$  (above), and the values of all the  $L^3$  norms (below) when  $\eta_k$  varies

Moreover unlike first generation wavelets, needlets do not form an orthonormal basis, but only a redundant frame. This leads to some specific difficulties for the study of the lower bound of the minimax risk. So we needed to prove the two new following results.

First we need an upper bound for the scalar products between needlets. This is given by Lemma 1.

**Lemma 1.** *We have:*

1.  $\forall j, j', k, l$  such that  $|j' - j| \geq 2$ ,  $\langle \psi_{j,\eta_k}, \psi_{j',\eta_l} \rangle = 0$ .
2.  $\forall \zeta > 0$ ,  $\exists c_\zeta$  such that  $\forall j, j', k, l$  with  $|j' - j| \leq 1$ :  $|\langle \psi_{j,\eta_k}, \psi_{j',\eta_l} \rangle| \leq \frac{c_\zeta}{(1+|k-2^{j-j'}|)^{\zeta}}$ .

Secondly we need a lower bound for the  $L^p$  norm of linear combinations of needlets. Note that a result as general as the upper bound of Theorem 5 is impossible. Indeed, for instance with the non null coefficients  $\sqrt{b_{j,\eta_k}}$  introduced in the definition of the needlets, one can check that:  $\sum_{k=1}^{2^j} \sqrt{b_{j,\eta_k}} \psi_{j,\eta_k} = 0$ . However we establish the following result for needlets with a large enough distance between the indexes of the  $\eta$ 's, in the case where  $p$  is an even integer:

**Theorem 7.** *Let  $p \in 2\mathbb{N}^*$ . Then there exists a constant  $c_p > 0$  and an integer  $n_p$  such that for any collection of numbers  $\{\lambda_k : k \in I_j\}$ ,  $j \geq 0$ , where  $I_j \subset \{1, 2, \dots, 2^j\}$*

and  $k, l \in I_j, k \neq l \implies |k - l| \geq n_p$ ,

$$\left\| \sum_{k \in I_j} \lambda_k \psi_{j, \eta_k} \right\|_{\mathbb{L}^p(\mu)}^p \geq c_p \sum_{k \in I_j} |\lambda_k|^p \|\psi_{j, \eta_k}\|_{\mathbb{L}^p(\mu)}^p.$$

*Proof of Lemma 1.* As indicated previously, the needlets are defined as:  $\psi_{j, \eta} = \sum_{l=2^{j-2}+1}^{2^j-1} c_{j, \eta, l} P_l(x)$ , with coefficients  $c_{j, \eta, l} = a(l/2^{j-1}) P_l(\eta) \sqrt{b_{j, \eta}}$ . So if  $|j' - j| \geq 2$  then  $\{2^{j-2} + 1, \dots, 2^j - 1\} \cap \{2^{j'-2} + 1, \dots, 2^{j'} - 1\} = \emptyset$ , and  $\langle \psi_{j, \eta_k}, \psi_{j', \eta_l} \rangle = 0, \quad \forall (k, l)$ .

For the second part of the lemma we use Theorem 4. For any  $\delta$  there exists  $c_\delta$  such that for all  $j, k$ :

$$|\psi_{j, \eta_k}(\cos \theta)| \leq c_\delta \frac{1}{\sqrt{\omega_{\alpha, \beta}(2^j, \cos \theta)}} \frac{2^{j/2}}{(1 + 2^j |\theta - \frac{\pi k}{2^j}|)^\delta}, \quad 0 \leq \theta \leq \pi.$$

We recall that  $\omega_{\alpha, \beta}(x) = (1-x)^\alpha (1+x)^\beta$ , and  $\omega_{\alpha, \beta}(2^j; x) = (1-x+2^{-2j})^{\alpha+1/2} (1+x+2^{-2j})^{\beta+1/2}$ . For a given  $\zeta > 0$  and  $j, j', k, l$  such that  $|j' - j| \leq 1$ , we use this inequality for  $|\psi_{j, \eta_k}|$  with  $\delta = \zeta + 2$  and for  $|\psi_{j', \eta_l}|$  with  $\delta = \zeta$ . Noticing that  $\omega_{\alpha, \beta}(2^j, \cos \theta) \asymp \omega_{\alpha, \beta}(2^{j'}, \cos \theta)$  we obtain:

$$\begin{aligned} |\langle \psi_{j, \eta_k}, \psi_{j', \eta_l} \rangle| &\leq c 2^j \int_0^\pi \frac{\omega_{\alpha, \beta}(\cos \theta)}{\omega_{\alpha, \beta}(2^j, \cos \theta)} \frac{\sin \theta d\theta}{(1 + 2^j |\theta - \frac{\pi k}{2^j}|)^{\zeta+2} (1 + 2^{j'} |\theta - \frac{\pi l}{2^{j'}}|)^\zeta} \\ &\leq c \frac{I_{j, k, \alpha, \beta}}{(\min_{0 \leq \theta \leq \pi} f_{j, j', k, l}(\theta))^\zeta}, \end{aligned}$$

with  $f_{j, j', k, l}(\theta) = (1 + 2^j |\theta - \frac{\pi k}{2^j}|)(1 + 2^{j'} |\theta - \frac{\pi l}{2^{j'}}|)$ ,  $0 \leq \theta \leq \pi$ , and  $I_{j, k, \alpha, \beta} = 2^j \int_0^\pi \frac{\omega_{\alpha, \beta}(\cos \theta)}{\omega_{\alpha, \beta}(2^j, \cos \theta)} \frac{\sin \theta d\theta}{(1 + 2^j |\theta - \frac{\pi k}{2^j}|)^2}$ .

First we have:  $\min_{0 \leq \theta \leq \pi} f_{j, j', k, l}(\theta) = \min\{f_{j, j', k, l}(\frac{\pi k}{2^j}), f_{j, j', k, l}(\frac{\pi l}{2^{j'}})\} \geq 1 + \frac{\pi}{2^{j-j'}} |k - 2^{j-j'} l| \geq c(1 + |k - 2^{j-j'} l|)$ . Secondly let us divide  $I_{j, k, \alpha, \beta}$  into two terms:

$I_{j,k,\alpha,\beta} = I_{j,k,\alpha,\beta}^1 + I_{j,k,\alpha,\beta}^2$ , with:

$$\begin{aligned} I_{j,k,\alpha,\beta}^1 &= 2^j \int_0^{\frac{\pi}{2}} \frac{\omega_{\alpha,\beta}(\cos \theta)}{\omega_{\alpha,\beta}(2^j, \cos \theta)} \frac{\sin \theta d\theta}{(1 + 2^j|\theta - \frac{\pi k}{2^j}|)^2}, \\ I_{j,k,\alpha,\beta}^2 &= 2^j \int_{\frac{\pi}{2}}^{\pi} \frac{\omega_{\alpha,\beta}(\cos \theta)}{\omega_{\alpha,\beta}(2^j, \cos \theta)} \frac{\sin \theta d\theta}{(1 + 2^j|\theta - \frac{\pi k}{2^j}|)^2} \\ &= 2^j \int_0^{\frac{\pi}{2}} \frac{\omega_{\alpha,\beta}(-\cos \theta)}{\omega_{\alpha,\beta}(2^j, -\cos \theta)} \frac{\sin \theta d\theta}{(1 + 2^j|\pi - \theta - \frac{\pi k}{2^j}|)^2} \\ &= 2^j \int_0^{\frac{\pi}{2}} \frac{\omega_{\beta,\alpha}(\cos \theta)}{\omega_{\beta,\alpha}(2^j, \cos \theta)} \frac{\sin \theta d\theta}{(1 + 2^j|\theta - \frac{\pi(2^j-k)}{2^j}|)^2} \\ &= I_{j,2^j-k,\beta,\alpha}^1. \end{aligned}$$

We have:  $\sin \theta \omega_{\alpha,\beta}(\cos \theta) = \sin \theta (2 \sin^2(\theta/2))^\alpha (2 \cos^2(\theta/2))^\beta \leq c_1 \theta^{2\alpha+1}$ , for all  $0 \leq \theta \leq \frac{\pi}{2}$ , and:

$$\omega_{\alpha,\beta}(2^j, \cos \theta) = (2 \sin^2(\theta/2) + 2^{-2j})^{\alpha+1/2} (2 \cos^2(\theta/2) + 2^{-2j})^{\beta+1/2} \geq c_2 \theta^{2\alpha+1}.$$

Thus  $I_{j,k,\alpha,\beta}^1 \leq c 2^j \int_0^{\frac{\pi}{2}} \frac{d\theta}{(1+2^j|\theta - \frac{\pi k}{2^j}|)^2} \leq c \int_0^{\frac{\pi 2^j}{2}} \frac{d\theta}{(1+|\theta - \pi k|)^2} \leq C$ , since  $\int_{-\infty}^{+\infty} \frac{d\theta}{(1+\theta)^2}$  is finite, and the same goes for  $I_{j,k,\alpha,\beta}^2$ .

Thus there exists  $C(\alpha, \beta) > 0$  such that for all  $(j, k)$ :  $I_{j,k,\alpha,\beta} \leq C(\alpha, \beta)$ , which completes the proof of the lemma.  $\square$

*Proof of Theorem 7.* Let  $p \in 2\mathbb{N}^*$  and  $I_j \subset \{1, 2, \dots, 2^j\}$ . We have the following decomposition:  $\|(\sum_{k \in I_j} \lambda_k \psi_{j,\eta_k})\|_{\mathbb{L}^p(\mu)}^p = A + B$ , where:

$$\begin{aligned} A &= \sum_{k \in I_j} \lambda_k^p \|\psi_{j,\eta_k}\|_{\mathbb{L}^p(\mu)}^p, \\ B &= \sum_{(p_k)_{k \in I_j} \in \Lambda} \frac{p! \prod_{k \in I_j} \lambda_k^{p_k}}{\prod_{k \in I_j} p_k!} \int_{-1}^1 \left( \prod_{k \in I_j} \psi_{j,\eta_k}^{p_k}(x) \right) \mu(x) dx, \end{aligned}$$

and  $\Lambda = \{(p_k)_{k \in I_j} \mid p_k \in \mathbb{N}, \sum_{k \in I_j} p_k = p \text{ and } \exists u \neq v \text{ such that } p_u > 0 \text{ and } p_v > 0\}$ .

Let us introduce the functions  $\varphi_{j,k}(x) = \frac{1}{\sqrt{\omega_{\alpha,\beta}(2^j, x)}} \frac{2^{j/2}}{(1+2^j|\arccos x - \frac{\pi k}{2^j}|)^{\frac{2}{s}}}$ , for some  $0 < s < \min\{1, \frac{p}{\alpha\sqrt{\beta+1}}\}$ . For  $(p_k)_{k \in I_j} \in \Lambda$ , we use Theorem 4 with  $l = \frac{2}{s} + 1$  for every  $\psi_{j,\eta_k}$ ,  $k \in I_j$ . There exists  $C$  such that:

$$\prod_{k \in I_j} |\psi_{j,\eta_k}(\cos \theta)|^{p_k} \leq C \prod_{k \in I_j} \varphi_{j,k}(\cos \theta)^{p_k} \prod_{k \in I_j} \frac{1}{(1 + 2^j|\theta - \frac{\pi k}{2^j}|)^{p_k}}.$$

Let  $u, v \in I_j$ ,  $u \neq v$  such that  $p_u > 0$  and  $p_v > 0$ , and let  $n_{\inf} = \min_{k,l \in I_j, k \neq l} |k - l|$ . We have:

$$\prod_{k \in I_j} (1 + 2^j|\theta - \frac{\pi k}{2^j}|)^{p_k} \geq (1 + 2^j|\theta - \frac{\pi u}{2^j}|)(1 + 2^j|\theta - \frac{\pi v}{2^j}|) \geq c|u - v| \geq cn_{\inf}.$$

Thus we obtain:

$$\begin{aligned} \sum_{(p_k)_{k \in I_j} \in \Lambda} \frac{p! \prod_{k \in I_j} |\lambda_k^{p_k}|}{\prod_{k \in I_j} p_k!} \prod_{k \in I_j} |\psi_{j,\eta_k}|^{p_k} &\leq \frac{C}{n_{\inf}} \sum_{(p_k)_{k \in I_j} \in \Lambda} \frac{p! \prod_{k \in I_j} |\lambda_k|^{p_k}}{\prod_{k \in I_j} p_k!} \prod_{k \in I_j} \varphi_{j,\eta_k}^{p_k} \\ &\leq C \frac{(\sum_{k \in I_j} |\lambda_k| \varphi_{j,\eta_k})^p}{n_{\inf}}. \end{aligned}$$

Now let us proceed similarly to the sketch of the proof of theorem 5 available in Kerkyacharian, Picard, Petrushev, and Willer (2007). Let us recall the two main tools.

First, consider the maximal operator  $(M_s f)(x) = \sup_{J \ni x} \left( \frac{1}{|J|} \int_J |f(u)|^s du \right)^{1/s}$ , where the supremum is taken over all intervals  $J \subset [-1, 1]$  which contain  $x$ ,  $s > 0$ , and  $|J|$  denotes the length of  $J$ . Then one can infer the following bound from the Fefferman-Stein maximal inequality (see Fefferman and Stein (1971)). If  $0 < p, r < \infty$  and  $0 < s < \min\{p, r, \frac{p}{\alpha\sqrt{\beta+1}}\}$ , then for any sequence of functions  $(f_k)$  on  $[-1, 1]$

$$\left\| \left( \sum_k (M_s f_k)^r \right)^{1/r} \right\|_{\mathbb{L}^p(\mu)} \leq C \left\| \left( \sum_k |f_k|^r \right)^{1/r} \right\|_{\mathbb{L}^p(\mu)}.$$

Secondly set  $\eta_0 = 1$  and  $\eta_{2^j+1} = -1$ , denote  $I_k = [\frac{\eta_k + \eta_{k+1}}{2}, \frac{\eta_k + \eta_{k-1}}{2}]$  and put  $H_k = h_k 1_{I_k}$  with  $h_k = \left( \frac{2^j}{\omega_{\alpha,\beta}(2^j, \eta_k)} \right)^{1/2}$ , where  $1_{I_k}$  is the indicator function of  $I_k$ . Then  $\|H_k\|_{\mathbb{L}^p(\mu)} \asymp \|\psi_{j,\eta_k}\|_{\mathbb{L}^p(\mu)}$ , and one shows in Kerkyacharian, Picard, Petrushev, and Willer (2007) that for any  $s > 0$

$$\varphi_{j,\eta_k}(x) \leq c(M_s H_k)(x), \quad x \in [-1, 1], \quad \forall k = 1, 2, \dots, 2^j, j \geq 0.$$

We use these two results, with  $f_k = H_k$  and  $r = 1$ . Noticing that the  $(H_k)$  have disjoint supports, we obtain:

$$\begin{aligned} \left\| \sum_{k=1}^{2^j} |\lambda_k| \varphi_{j,\eta_k} \right\|_{\mathbb{L}^p(\mu)}^p &\leq C \left\| \sum_{k=1}^{2^j} |\lambda_k| H_k \right\|_{\mathbb{L}^p(\mu)}^p = C \sum_{k=1}^{2^j} |\lambda_k|^p \|H_k\|_{\mathbb{L}^p(\mu)}^p \\ &\leq C' \sum_{k=1}^{2^j} |\lambda_k|^p \|\psi_{j,\eta_k}\|_{\mathbb{L}^p(\mu)}^p. \end{aligned}$$

So finally there exists  $C > 0$  such that  $|B| \leq C \frac{A}{n_{\inf}}$ , and if we impose the following condition on  $I_j$ :  $n_{\inf} \geq 2C$ , then we obtain  $|B| \leq \frac{1}{2}A$ , and thus:

$$\left\| \left( \sum_{k \in I_j} \lambda_k \psi_{j,\eta_k} \right) \right\|_{\mathbb{L}^p(\mu)}^p \geq \frac{1}{2} \sum_{k \in I_j} \lambda_k^p \|\psi_{j,\eta_k}\|_{\mathbb{L}^p(\mu)}^p.$$

□

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